ADDRESSING STUDENT PERFORMANCE IN THE CLASSROOM: A CASE STUDY OF THE UNIVERSITY OF ALASKA FAIRBANKS SUPPLEMENTAL INSTRUCTION PROGRAM

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A

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Abstract

The Supplemental Instruction (SI) program, developed and headquartered at the University of Missouri Kansas City, is a peer-to-peer mentorship program that seeks to aid post-secondary education students in passing historically difficult courses. The University of Alaska Fairbanks Supplemental Instruction program was established in 2003, and to date no external study has been completed as to its effectiveness despite the university's unique student population. To empirically evaluate the program's main user groups and impact on final course grade, three models were created: a probit model identified the demographic factors that led to a student self-selecting to participate; a negative binomial regression model was used to predict the number of SI sessions students attended; and an ordered probit model quantified the effect of SI attendance on final course grades. The results suggest that the program had a positive impact on final grades, with SI attendees being approximately 92% more likely to receive an A, and 94% less likely to receive a D or an F, than non-attendees. Older and married students were consistently found to be more likely to participate, as were students with large high school grade point averages. However, minority males were found to be almost 9% less likely to participate in SI than their white male counterparts.

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Chapter 1 Introduction

Since the inception of institutionalized education, educators and administrators alike have attempted to isolate the perfect formula to maximize tutorial impact on a student's comprehension of course material. Though various tutoring methods have been en vogue at various points over the past century, several modern learning paradigms coalesced in the late 1970s with the creation of the Supplemental Instruction (SI) program (Loviscek & Cloutier, 1997). SI is a peer-to-peer mentorship program that seeks to aid post-secondary education students in passing historically difficult courses, and has been implemented at universities worldwide (University of Missouri Kansas City [UMKC], 2014).

Unlike more conventional tutoring practices—consisting of a student going to a course tutor's office hours for one-on-one assistance with a particular concept or homework problem—SI is a highly structured, copyrighted program method that emphasizes a holistic approach to student learning. Rather than a one-size-fits-all method, institutions are asked to identify those courses that have historically low pass rates, identified by the moniker "DWF," or Drop-Withdrawal-Fail. Tutors, or SI Leaders as they are referred to within the SI program framework, are then selected for these courses from a pool of undergraduate upperclassmen applicants that have already successfully completed one or more DWF course. Once trained and assigned to a DWF course, SI Leaders audit the class alongside the students that they assist, attending all lectures, taking notes, and completing required readings. The SI Leader then holds voluntary "SI Sessions" for the class, where they lead discussion on course material and engage in any number of group teaching techniques to help students independently arrive at the answers to their questions. Attendance to these sessions is kept strictly confidential, and faculty are not told which students did—or did not—attend. (UMKC, 2014)

Though innovative, SI represents a significant sunk cost to the institution not realized with conventional tutoring practices. Before establishing an SI franchise on campus, a university is required to send campus personnel who will be administering the program, typically some contingent of academic advisors or associated support staff, to receive SI certification at a two- to three-day training conference held at the University of Missouri Kansas City, the birthplace and headquarters of SI (UMKC, 2014). The training course fee and travel costs are borne by the university. If staff changes occur, any new program administrators are also required to become certified. Furthermore, the university, in addition to the SI Leader's hourly salary, subsidizes fees and all associated materials needed for the Leader to audit the DWF course.

Based on this cost, properly identifying the factors that dictate whether a student attends SI can have real-world policy implications: if a university is attempting to utilize SI as an academic success and retention mechanism for underserved and/or underrepresented populations (e.g., first generation college student, females in STEM majors, ethnic minorities), yet only overrepresented student groups are attending SI sessions, an evaluation of the program's funding might be warranted. If the reverse is true, then universities will have empirical evidence to justify directing more money towards the expansion of the program beyond just DWF courses.

To date, no in-depth study has been completed as to the effectiveness of the SI program at the University of Alaska Fairbanks (UAF), and what the academic results are for those students who self-select to participate in SI sessions. This thesis examines UAF as a case study—using empirical analysis, the statistically significant impact that SI attendance has on students' final course grades is examined, as are the demographic factors that lead to a student self-selecting to participate in SI. Though SI has been proven to have a positive impact on final grades and next-semester reenrollment for "high-risk student" groups, it is important to note that in previous studies students were classified as “high-risk” based on their prior academic performance, not their demographic background (Blanc, DeBuhr, & Martin, 1983).

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Chapter 2 Literature Review

Supplemental Instruction has been repeatedly proven to have a statistically significant positive effect on student performance in the courses where it has been implemented—this effect has been shown to hold true across different universities on both the national and international stage Con. The number of SI courses and semesters studied to reach this conclusion vary across the literature. Additionally, the number of sessions used to define SI participation varies greatly between studies. In earlier literature, it was generally concluded that students needed to attend a minimum of five sessions to realize the positive effects of SI, and thereby be defined as an SI attendee (Ashwin, 2003; Martin & Arendale, 1992; McCarthy, Smuts, & Cosser, 1997). However, more recent studies have used between one and 12 sessions of student participation to define attendance, yet "[d]ecisions for the cutoff number of sessions were largely arbitrary and unsubstantiated" (Dawson, van der Meer, Skalicky, & Cowley, 2014, p. 619).

The research methods for evaluating SI significantly vary, with the vast majority of studies employing qualitative methods. However, when quantitative methods were used, no one model or modeling technique was found to be the standard—SI effectiveness has been studied by researchers of various disciplines, resulting in differing empirical approaches. The most frequently observed models are analysis of variance (ANOVA) and analysis of covariance (ANCOVA), with simultaneous equation models beginning to appear in more recent literature (Bowles & Jones, 2003; Bowles, McCoy, & Bates, 2008; Dawson et al., 2014; Hensen & Shelley, 2003; Hodges, Dochen, & Joy, 2014; Parkinson, 2009). For those studies that controlled for self-selection into SI, the most commonly used metric was pretertiary achievement (Dawson et al., 2014).

Despite the positive results that seem to be consistently found when an SI program is studied, several articles have been published over the past two decades cautioning the SI research community to apply cohesive methods to the data collection and analysis process, as well as recommending the inclusion of several understudied variables (Ashwin, 2003; Dawson et al., 2014; Kochenour et al., 1997; McCarthy et al., 1997). In their review of SI literature, Dawson et al. (2014) cite three major dissident studies: McCarthy et al. (1997), Kochenour et al. (1997), and Ashwin (2003). In the first of these, McCarthy et al. (1997) found that "the statistical analyses deployed in the previous studies of the effectiveness of SI are not sophisticated enough to account for the many factors which may influence students' final results" (p. 221). To overcome this, they urge "a move towards a qualitative approach involving a consideration of the place of SI in the total learning experience of the individual student" (McCarthy et al., 1997, p. 221). Kochenour et al. (1997) argues that, "Of the research that supports SI, much is anecdotal, is based on small or nonrepresentative samples, or does not adequately consider student ability as a possible explanation for the apparent 'effect' of SI" (p. 578). Additionally, Ashwin (2003) finds that, "There has been no consideration of the ways in which students are assessed and whether an improvement in students' academic performance is also an indication of an improvement in the *quality* of students' learning, partly because this relationship can only be investigated in a single context" (p. 164).

To this criticism, Dawson et al. (2014) add their own. Through their strategic review of worldwide SI literature between 2001 and 2010, they found only 29 of over 1,400 articles that satisfied their basic inclusion criteria, which included such parameters as whether the article was peer-reviewed, published, included student outcomes, SI group sessions were held, etc.. Of these articles, SI was shown to be effective in increasing the final course grade and course pass rate of participants. SI also appears to positively impact retention and graduation rates, but as very minimal research has been done on this aspect, the authors warn that this result should be taken with caution. However, they ultimately find that no article currently existing in the literature is "supported by a gold standard study involving random assignments to groups and sufficient detail about methodology, participants, and the SI intervention in practice" (Dawson et al., 2014, p. 635).

The above articles outline that there is concern within the community that SI research methods have not necessarily been systematically and consistently applied among all case studies. Additionally, the overall quality of research within the field was called into considerable question when less than 1% of currently published articles satisfied the rudimentary criteria set forth by Dawson et al. (2014). As SI has been implemented, adjusted, and subsequently studied on the international stage, the resulting body of literature has become a patchwork of varying empirical methods, modeling techniques, and degrees of analytical rigor. Accordingly, this research aims to conform to the basic SI research standardization principles outlined by Dawson et al. (2014), as well as seeks to advance the research methods in the field by employing the use of empirical models not yet found in the literature.

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Chapter 3 Data

As no prior case study has been done on the UAF Supplemental Instruction program, an original dataset was compiled to examine the academic and socio-demographic factors behind SI attendance and overall program effectiveness. The diverse nature of the campus' student body creates a unique student sample—as of Fall 2015, the median student age was 25, 18.5% self-identified as Alaska Native/American Islander, 58.7% of all students were female, and students were enrolled from 49 US states and 45 foreign countries (University of Alaska Fairbanks [UAF], 2015).

According to available records, the SI program at UAF was implemented in approximately Fall 2003, with various DWF courses cycling through the SI offerings. For example, School of Management, which participated early on in the UAF SI initiative with economics courses, now does not offer any courses with an SI component. Due to turnover in staff, the campus SI attendance and tutor records over this period are incomplete, but three main units on campus are currently maintaining records: the Academic Advising Center (AAC), the Chemistry Learning Center (CLC), and the College of Engineering and Mines (CEM) Student Advising office. The AAC facilitates the majority of SI courses on campus, and has records—which include courses offering SI, student attendance for each SI session logged by UAF identification number, and student final grade in the course—back to Spring 2011. CLC has the same records for its course offerings from Fall 2012 onward, and CEM only has course records from Fall 2013 onward. Additionally, the majority of courses offering SI are entry level, falling either into the category of core curriculum or major requirements.

After collecting session attendance records and final course grades for each known SI course (for a more detailed discussion of the data collection procedures, please refer to Appendix

A), student demographic data was joined to each observation. Due to external constraints, UAF student demographic data records were only available for Spring 2011 through Spring 2014, thereby limiting the longitudinal scope of the study. The resulting dataset had a total of 1,876 individual students. Based on the longitudinal nature of the data, numerous students enrolled in more than one course offering SI—usually in sequential courses such as chemistry or biology—resulting in a total of 3,081 unique observations.

As can be seen in Table 1, the master dataset was comprised of a total of 14 courses that offered SI between Spring 2011 and Spring 2014. With the exception of one, all SI courses were offered within STEM fields. Additionally, it is important to note that half of the courses only offered SI for one semester. Institutional records do not exist to explain the variation of SI course offerings between semesters, but it is believed that budget constraints, staff turnover, and a lack of qualified SI leaders are in large part responsible.

Table 2 indicates the main variables found in the master dataset, as well as their associated descriptive statistics. Before analyzing the overall composition of the dataset, it is

Table 1. *UAF Courses Offering SI, Spring 2011 Through Spring 2014*

Class Number	Course Title	Number of Semesters
BIOL 111X	Human Anatomy and Physiology I (AY11-12)	2
BIOL 112X	Human Anatomy and Physiology II (AY11-12)	3
BIOL 115X	Fundamentals of Biology I	2
BIOL 116X	Fundamentals of Biology II	2
BIOL 213X	Human Anatomy and Physiology I (AY13-14)	1
BIOL 214X	Human Anatomy and Physiology II (AY13-14)	1
CHEM 105X	General Chemistry I	6
CHEM 106X	General Chemistry II	3
ES 210X	Dynamics	1
ES 301X	Engineering Analysis	1
ES 346X	Basic Thermodynamics	1
HIST 100X	Modern World History	2
MATH 103X	Concepts and Contemporary Applications of Mathematics	1
MATH 262X	Calculus for Business and Economics	1

Table 2: *Description of Key Dataset Variables*

Variable Name	Description	Descriptive Statistics
AttendD	=1 if student attended SI at least one time during the semester	Mean=0.288 Std Dev=0.453
Total_Attended	Number of SI sessions student attended during the semester	Mean=0.875 Std Dev =2.276
AttFem	=1 if student attended SI at least one time during the semester and is female	Mean=0.142 Std Dev =0.349
AttMin	=1 if student attended SI at least one time during the semester and self-identified as a member of an ethnic minority group	Mean=0.043 Std Dev =0.203
Rfinal	Final grade student received in course; 1=F, 2=D, 3=C, 4=B, 5=A	Mean=3.337 Std Dev =1.238
Randomid	Unique, randomly generated identifier assigned to each student	N/A
Identifier	Unique identifier for each course in dataset	N/A
Female	=1 if student is female	Mean=0.466 Std Dev =0.499
Married	=1 if student is married	Mean=0.071 Std Dev =0.258
Age	Student age during the observed semester	Mean=21.714 Std Dev =5.190
STEM	=1 if student was a declared STEM major	Mean=0.609 Std Dev =0.488
SAT10	=1 if student scored within the top 10 percentile on their SAT	Mean=0.027 Std Dev =0.161
ACT10	=1 if student scored within the top 10 percentile on their ACT	Mean=0.080 Std Dev =0.271
HSGPA	High school GPA	Mean=3.409 Std Dev =0.515
Minority	=1 if student self-identified as a member of an ethnic minority group	Mean=0.163 Std Dev =0.370
Native	=1 if student self-identified as a Native American, Alaska Native, or Native Pacific Islander	Mean=0.081 Std Dev =0.274
AKNative	=1 if student self-identified as an Alaskan Native	Mean=0.071 Std Dev =0.258
hsrural	=1 if student graduated from a high school in rural Alaska	Mean=0.224 Std Dev =0.417
hsurb	=1 if student graduated from a high school in urban Alaska	Mean=0.488 Std Dev =0.500
hsout	=1 if student graduated from a United States high school outside of Alaska	Mean=0.236 Std Dev =0.425
hsint	=1 if student graduated from a foreign high school	Mean=0.023 Std Dev =0.150
Fem_white	=1 if student self-identified as a white female	Mean=0.264 Std Dev =0.441
Fem_min	=1 if student self-identified as a minority female	Mean=0.055 Std Dev =0.227
Male_white	=1 if student self-identified as a white male	Mean=0.321 Std Dev =0.467
Male_min	=1 if student self-identified as a minority male	Mean=0.062 Std Dev =0.241

important to note how certain variables were defined. One of the key metrics supplied through the available data to identify prior academic performance is Scholastic Aptitude Test (SAT) and American College Testing (ACT) scores. As the two tests use different score scales and are both accepted for admission to UAF, dummy variables were created to identify those students who scored within the top 10 percentile of the SAT or ACT (The College Board, 2014; The ACT, 2014). As no variable currently exists in the UAF student database to capture cumulative grade point average (GPA) for each student in every semester, and as a new variable could not be coded due to staffing shortages, proxy variables were used to control for student prior academic performance and ability. These included high school GPA, and ranking on the SAT and ACT tests. An additional dummy variable, *STEM*, was created for those students who had a declared major in Science, Technology, Engineering, and Mathematics (STEM) fields.

In order to identify whether Alaskan students graduated from an urban or rural high school, the 2010 US Census was used. Based on the approved urban area criteria, the Census recognized a total of 14 Alaskan communities as urban, with all other settlements classified as rural (United States Census Bureau, 2012). Accordingly, the *hsrural* and *hsurb* dummy variables were created by cross-referencing the student's high school location with the 14 urban communities.

When SI was integrated into a course, the majority of students did not participate. Of the 887 students that did attend SI, approximately 44% only attended SI once, and roughly 22% attended two sessions. The remaining 34% of attendees went to three or more sessions, with a maximum observation of 23 sessions. The master dataset does in some cases include multiple observations for the same individual, yet these only occur when the student was enrolled in two or more courses that offered SI—for example, a student could be enrolled in BIOL 111X in the

Fall semester, and subsequently enrolled in BIOL 112X in the Spring. As each course is an independent event, SI attendance is reported in aggregate.

Based on the large range of values, attendance records were also divided into six separate categories in order to increase the number of observations in each grouping. As may be expected, the number of observations present in each category decreases as the number of SI sessions increases. This indicates that of the courses that offered SI, roughly 7% of enrolled students attended more than three sessions, with approximately 1% of the sample attending 11 or more. In all, approximately 29% of students participated in SI when it was made available.

The remaining variables in the dataset were demographic in nature. In regards to gender, 1,435 of the 3,081 total observations (or approximately 46.58%) were female students, resulting in an almost even gender split for the overall dataset. However, only 23.3% of overall observations were females who were also STEM majors, creating a disparity between males and females enrolled in STEM courses.

Additionally, as the UAF campus is diverse, special attention was given to the ethnic breakdown of the included observations. As students reported a total of 25 different ethnic categories, these were combined into three main categories with numerous subcategories. Of these, 1,091 students identified as white, 503 identified as a race other than white, and 744 chose not to specify their ethnicity. It is also of interest to note that 46.04% of individual students graduated from an urban Alaskan high school, compared to approximately 23% graduating from a rural Alaskan school. Students from rural Alaska were also proportionally the least likely to attend SI when compared to their urban, non-Alaskan, and international peers. More information on attendance rates and ethnicity can be found in Appendix A.

Limitations exist for the master dataset, resulting in decreased explanatory power for some variables. Foremost among these limitations are missing observations. As mentioned previously, student demographic information was not available for the 2015-2016 academic year (AY), thereby reducing the number of semesters included in the study from nine to seven. Of the observations that were included, incomplete demographic records further contributed to the missing data problem. Student scores for the SAT and ACT tests were not provided for AY14-15, meaning that scores from incoming students that academic year were not captured. This lead to 542 missing observations for the *SAT10* and *ACT10* variables. Additionally, high school graduation and performance information is not captured by the UAF Admissions Office for every student—this is particularly true for transfer students, students from outside of Alaska, and students who did not graduate from a traditional high school—which created missing high school demographics for some students at all time periods. There are 578 observations missing for HSGPA, and 90 observations missing high school location information (of these, 75 are from students who graduated with a GED, with the remaining 15 being a combination of home school, correspondence school, and students with an unknown high school graduation status).

Missing observations were also generated for the ordinal variable *Rfinal*. The variable was coded based on the typical American academic grade scale of F through A, but not all observations fell within these values. 222 missing observations were created, with 202 being caused by students withdrawing from the course after the academic course drop deadline (resulting in the student receiving a W in the course), and the remaining 20 values being a combination of course audits and incomplete grades.

In addition to the missing data limitations to *SAT10* and *ACT10*, there are also broader issues with capturing SAT and ACT scores for UAF students. In order to apply for undergraduate admission to the campus, "freshman and transfer applications with fewer than 30 semester credit hours must submit the results of either the ACT Plus Writing (preferred) or the SAT examination" (UAF, 2016b). As such, the college aptitude tests are not required for transfer students who have earned more than 30 credits, and those students who do fall under this admissions criterion must only submit scores for one test or the other. Even if complete information was provided from the Registrar's Office regarding students' reported SAT or ACT scores, there would regardless be a significant contingent of students who either do not have any reported scores, or only have scores for one of the two tests. In the dataset, there are 1,903 observations missing ACT scores, and 1,676 missing SAT scores. To help manage this disparity, the *SAT10* and *ACT10* dummy variables were used to identify those students who had reported scores for the test, and subsequently had scored within the national top 10 percentile. However, the compounding factors behind the missing observations for the test scores might limit the explanatory power of these variables.

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Chapter 4 Analysis

This case study sought to address three key research questions: what factors drove a student to participate in SI; what factors determined how many SI sessions a student would attend; and what was the impact of attending SI on final course grade. As each question targeted a different group of dependent and independent variables, three separate models were used. The selection, composition, and basis for the respective probit, negative binomial, and ordinal probit models is discussed below. It should also be noted that based on the variation in SI course offerings, all semester and courses were compiled and run as cross-sectional data.

When examining which factors contributed to a student's decision to participate in SI, a relatively basic dependent variable—indicating simply whether or not the student attended—must be used. Accordingly, the attendance dummy variable *AttendD* was selected. Due to the nature of having a dependent variable that, by definition, can only assume two values, a linear regression model cannot be used. Instead, it is necessary to employ a model that predicts the probability of the dummy variable being one, given the explanatory variables included in the model. Binary dependent variable models are not widely found within the SI literature, with only two articles—utilizing a bivariate probit model and a simultaneous limited dependent variable model, respectively—meeting the basic criteria to be included in the Dawson et al. (2014) study. As both of these models are variations of a standard probit model—a nonlinear binary responses model using maximum likelihood estimation—the probit was selected to model *AttendD*. The general equation for a probit model is as follows:

$$\Pr(y_j \neq 0 \mid \mathrm{x}_j) = \Phi(\mathrm{x}_j\beta)$$

"where Φ is the standard cumulative normal" (StataCorp, 2013b). The probit model predicts the probability of the dependent variable being equal to one using a standard normal distribution.

Based on Bowles & Jones (2003, 2004) models' inclusion of ACT scores and gender as independent variables, the probit model for *AttendD* takes the following form:

$$\Pr(\text{AttendD}=1)=\Phi(\beta_0+\beta_1\text{age}+\beta_2\text{STEM}+\beta_3\text{SAT10}+\beta_4\text{ACT10}+\beta_5\text{married} \quad (1)$$
$$+\beta_6\text{fem\_white}+\beta_7\text{fem\_min}+\beta_8\text{male\_min})+\varepsilon$$

SAT10 and *ACT10* were included as proxy variables for pretertiary achievement and inherent student ability, and several demographic variables were added to help explain what factors influenced a student's decision to attend SI. Foremost among these are a set of interaction terms between gender and ethnicity. The term with the largest number of observations, white males, was set as the base group. Student age in the semester the course was offered, martial status, and whether the individual was a declared STEM major were also included.

In addition to having a dependent binary SI attendance variable, this study was also interested in trying to determine which personal characteristics help predict how many SI sessions, if any, a student attended. Accordingly, this required the use of a count variable, *Total_Attended*—which indicated the number of SI sessions a student attended—as the dependent variable. Since a count variable is more complex than a simple binary, it necessitates the use of a different model. There is little, if any, precedence in the SI literature for modeling a dependent count variable, with none of the articles in the Dawson et al. (2014) study employing such a model.

Though multiple count models were compared—including a poisson regression model (PRM), zero-inflated poisson (ZIP), and zero-inflated negative binomial (ZINB)—a negative binomial regression (NBRM) was selected based on the model fit statistics. As can be seen in

Figure 1, both the NBRM and ZINB have a superior data fit to the PRM and ZIP. This can largely be accounted for due to the overdispersion present in *Total_Attended*—2,194 of the 3,081 observations are equal to zero. However, as the model's independent variables are primarily binary, the logit component of the ZINB returns coefficients with large standard errors and minimal, if any, statistical significance. Additionally, the NBRM has a lower Pearson's score than ZINB when comparing predicted and actual probabilities, as well as a lower Bayesian information criterion (BIC) score.

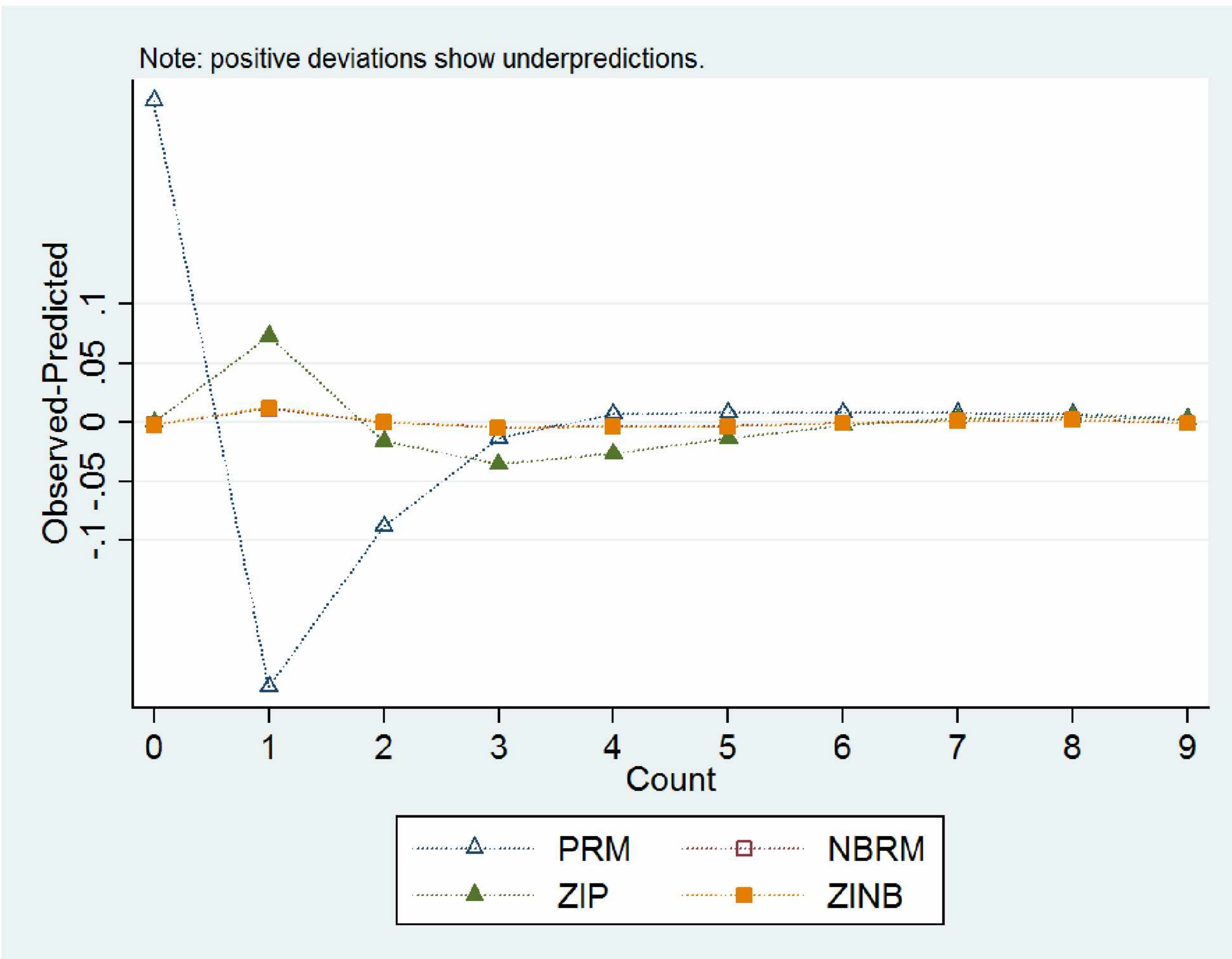

Figure 1. *Plotted Residuals from Tested Count Models on Total_Attended*

Below is the general equation for the negative binomial model, with the allowance that we "let y_{it} be the count for the tth observation in the ith group:

$$\Pr(Y_{it} = y_{it} \mid \mathbf{x}_{it}, \delta_i) = \frac{\Gamma(\lambda_{it} + y_{it})}{\Gamma(\lambda_{it})\Gamma(y_{it} + 1)} \left(\frac{1}{1+\delta_i}\right)^{\lambda_{it}} \left(\frac{\delta_i}{1+\delta_i}\right)^{y_{it}}$$

'where $\gamma_{it} \mid \delta_I \sim \text{gamma}(\lambda_{it}, \delta_i)$ with $\lambda_{it} = \exp(\mathbf{x}_{it}\beta + \text{offset}_{it})$ and δ_I is the dispersion parameter" (StataCorp, 2009, p. 367).

This model, similar to the probit, was concerned with the factors influencing SI attendance, and as a comparable dependent count variable model could not be found in the literature. Accordingly, Bowles & Jones (2003, 2004) were used to validate the inclusion of high school GPA and gender, with additional independent variables also added:

$$\text{Total\_Attended} = \beta_0 + \beta_1\text{fem\_min} + \beta_2\text{male\_white} + \beta_3\text{male\_min} + \beta_4\text{married} + \beta_5\text{age} + \beta_6\text{HSGPA} + v \quad (2)$$

As with the probit model, *married* and *age* were incorporated as explanatory variables to determine how many times a student attended SI. It was expected that married and older students would attend more SI sessions, ceteris paribus, based on their non-traditional student status and potential inability to attend other tutoring opportunities due to extracurricular commitments. The interaction terms between gender and ethnicity were also included; however, white females were used as the base group. This was done to provide a different explanatory aspect to the results than the probit, particularly as white females had the second largest number of observations. Additionally, females have been shown to be more likely to attend SI than their male peers (Loviscek & Cloutier, 1997; Rath, Peterfreund, Xenos, Bayliss, & Carnal, 2007).

After observing the factors influencing a student's decision to attend SI, the final model examined the final grade a student received in an SI course using the variable *Rfinal*. This model was used to quantify the statistically significant impact, if any, SI attendance had on a student's overall performance in the course. As with the dependent count variable model, no model could be found in the existing SI literature that utilized a dependent variable that was both categorical and ordered. Subsequently, an ordered probit model (oprobit) was selected based on its implementation in higher education and econometric research (Bauer & Riphahn, 2006; Daykin & Moffatt, 2002; Tolbert, 1985). The general equation for an oprobit model is:

$$\Pr(\text{outcome}_j = i) = \Pr(\kappa_{i-1} < \beta_1 x_{1j} + \beta_2 x_{2j} + \ldots + \beta_k x_{kj} + u_j \leq \kappa_i)$$

Where "the probability of observing outcome *i* corresponds to the probability that the estimated linear function, plus random error, is within the range of the cutpoints [κ] estimated for the outcome" (StataCorp, 2013a). Additionally, "u_j is assumed to be normally distributed…[and] κ_0 is taken as -∞, and κ_1 is taken as +∞" (StataCorp, 2013a).

The ultimate objective for the oprobit was to explain what factors influenced final course grades. Consequently, the model incorporated SI attendance variables in addition to various demographic factors and academic performance proxies:

$$\begin{aligned}\Pr(\text{Rfinal}_i = i) = \Pr(&\kappa_{i-1} < \beta_0\text{AttendD}+\beta_1\text{AttFem}+\beta_2\text{AttMin}+\beta_3\text{Female}+\beta_4\text{minority} \\ &+\beta_5\text{STEM}+\beta_6\text{age}+\beta_7\text{SAT10}+\beta_8\text{ACT10}+\beta_9\text{married}+\beta_{10}\text{hsrural} \\ &+\beta_{11}\text{hsout}+\beta_{12}\text{hsint}+u_j \leq \kappa_i)\end{aligned} \tag{3}$$

The model's main interest was quantifying the affect SI attendance had on final grades, therefore three separate attendance variables were included. The first, *AttendD*, looked simply at whether a student attended SI; the *AttFem* and *AttMin* interaction terms captured the SI attendance affect for females and minority groups, respectively. As with the two prior models, gender, age, and martial status were included as demographic factors, with *SAT10* and *ACT10* serving as proxies for prior academic performance and innate student ability. *STEM* and *minority* were added as additional demographic variables with explanatory power for the final grade received in the course. A final set of demographic dummy variables, high school location, were included as a means of controlling for pretertiary academic preparation, as intuitively students from rural Alaska might not be as prepared for college as their urban or non-Alaskan counterparts. Alaskan urban high school locations, which had the largest number of observations, was set as the base group.

Though coefficients and standard errors are reported for each independent variable, the oprobit also reports on the model's cutpoints, which are discussed below. This allows for interpretations on the cuts themselves—such as evaluating whether there is a statistically significant latent variable that determines whether a student receives an F or a D final grade—as well as the ability to generate the predicted probability of a student who attended SI falling into any particular cut (StataCorp, 2013a).

Chapter 5 Results

All models were estimated using STATA 12 software, with the first being the probit model with the dependent variable of *AttendD*. It should be noted that though all three of the following models were not run using panel data commands, clustering still occurred in the data due to each SI course offering being a unique entity. Unobserved variables—such as a differing homework policies among course instructors, or a recently rewritten syllabus—may have contributed to a different learning environment for each semester, even when the same course number was observed multiple times. As such, all models were clustered on the variable *identifier*, resulting in the reporting of cluster-robust standard errors.

Table 3. *Results of Probit Model Using Dependent Variable AttendD*[1]

VARIABLES	(1) AttendD	Marginal Effects
Age	0.0178***	0.00595***
	(0.00466)	(0.00154)
STEM†	0.0884	0.0296
	(0.0984)	(0.0333)
SAT10†	-0.278	-0.0931
	(0.227)	(0.0757)
ACT10†	-0.225***	-0.0751***
	(0.0763)	(0.0271)
married†	0.150*	0.0501*
	(0.0865)	(0.0291)
fem_white†	0.0156	0.00523
	(0.0800)	(0.0267)
fem_min†	-0.0157	-0.00524
	(0.127)	(0.0426)
male_min†	-0.267**	-0.0892**
	(0.114)	(0.0380)
Constant	-0.991***	
	(0.135)	
Observations	2,539	
Pseudo R^2	0.0118	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[1]Note that † indicates that the computed (dy/dx) value is for a discrete change of a dummy variable from 0 to 1.

Table 3 reports the full estimated results of the probit model, which seeks to identify the factors influencing a student's decision to attend SI. A total of 542 observations were dropped due to missing data in *SAT10* and *ACT10*, resulting in 2,539 observations being reported instead of the dataset total of 3,081. Though the signs on all variables makes intuitive sense and present as expected, of particular note are the four statistically significant variables. *Age* is positive and highly statistically significant, indicating that older students—which, based on UAF's median student age of 25, can be thought to include non-traditional students—are more likely to seek out help, thereby attending SI. Those students who score highly on the ACT likely either have high innate ability or are from academically-sound backgrounds, and as such feel more comfortable with the course content. This accounts for the negative and highly statistically significant result of *ACT10*. Married students are likely to be older—therefore corresponding with the results for *age*—and to have more family obligations and demands on their time than their single counterparts, causing them to use the academic resources available to them. Lastly, minority males have historically been a disenfranchised group, and as 158 of the 190 students in this group are under the age of 25 and unmarried, the statistically significant negative coefficient is not unexpected.

By examining the marginal effects of the independent variables, it becomes easier to quantify the predicted probability of students attending SI. For example, for each year older a student becomes, they are approximately 0.6% more likely to attend SI, all else equal. Married students are roughly 5% more likely to attend, students who scored within the top 10 percentile on their ACT exam are 7.5% less likely to attend, and male minority students are almost 9% less likely to attend. This last result is of particular note, as it indicates that male minority students are not a group that the UAF SI program has historically served. Interestingly, all female students, regardless of ethnicity, are more likely to attend SI, though this result is not statistically significant.

Turning now to the count data model that sought to identify the underlying demographic and academic components predicating how many SI sessions a student attended, the results of the negative binomial regression model are found in Table 4 below. 578 observations were dropped from the model due to missing data for *HSGPA*, resulting in 2,503 observations being included.

Table 4. *Results of NBRM Using Dependent Variable Total_Attended*

	(2)
VARIABLES	Total_Attended
fem_min	0.0470
	(0.211)
male_white	-0.186
	(0.133)
male_min	-0.497**
	(0.215)
married	0.320
	(0.292)
Age	0.0429***
	(0.0134)
HSGPA	0.228**
	(0.113)
Constant	-1.817***
	(0.603)
lnalpha	1.612***
	(0.110)
Observations	2,503

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As can be seen above, both *male_min* and *age* were again found to be statistically significant with the same sign as reported in the probit model. All else equal, minority males attended fewer SI sessions, with older students attending more. Additionally, HSGPA was positive and statistically significant, indicating that students with higher high school GPAs attended more SI sessions. This may indicate that higher achieving students are more likely to make the decision to attend SI, introducing a potential self-selection bias.

When interpreting the above estimates, it is important to first take the exponent of the coefficient. For example, male minority students are expected to attend 0.61 SI sessions (or less than one session) when compared to their white male counterparts, with the exponentiation of *age* and *HSGPA* resulting in 1.04 and 1.26, respectively. As such, for every year older a student is, they are expected to attend 0.04 more SI sessions. Additionally, for every incremental increase in *HSGPA*, SI attendance increases by 0.26 sessions. It is also of interest to note that the mean prediction estimate for the model, or the exponentiated value of the mean probability of how many SI sessions students are predicted to attend, is 2.27. As such, the average SI session count per student is predicted to be more than two.

In summary, prior academic achievement, age, and ethnicity are all factors that influence how many SI sessions a student will attend. These results are consistent with the prior model, which addressed a student's decision general of whether to attend SI at all. Interestingly, *married* is not found to be statistically significant when modeling on *Total_Attended*, despite its significance for *AttendD*.

The third and final model, which in part observes the outcome of SI attendance on final course grade, is presented in Table 5 below. Though the signs and significance of the coefficients can be interpreted, this model also provides significant value by observing the estimated cutpoint for each category of *Rfinal* and the resulting predicted probability of a student being present in any one grade category. It is also the largest of the models, with 13 independent variables—three of which measure differing aspects of the impact of SI attendance—included in the analysis.

Table 5. *Results of Ordered Probit Model Using Dependent Variable Rfinal*

VARIABLES	(3) Rfinal
AttendD	0.468***
	(0.0922)
AttFem	-0.183*
	(0.0971)
AttMin	0.0221
	(0.0768)
Female	0.118
	(0.0747)
minority	-0.186***
	(0.0527)
STEM	0.232***
	(0.0855)
Age	0.0134**
	(0.00613)
SAT10	0.708***
	(0.151)
ACT10	0.464***
	(0.0989)
married	0.165*
	(0.0985)
hsrural	-0.130***
	(0.0353)
hsout	-0.141**
	(0.0632)
hsint	0.136
	(0.128)
Constant cut1 (F to D)	-0.615***
	(0.198)
Constant cut2 (D to C)	-0.184
	(0.209)
Constant cut3 (C to B)	0.575***
	(0.211)
Constant cut4 (B to A)	1.499***
	(0.194)
Observations	2,344
Pseudo R^2	0.0250

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Ten of the 13 explanatory variables were found to be statistically significant, meaning that they have a measurable impact on the final course grade observed for each student. In particular, two of the three SI attendance variables were found to be statistically significant. The large, positive coefficient of *AttendD* indicates that students who attended SI ultimately received a higher final grade in the course. This result is found to be significant at the 1% level, and is strong evidence that the UAF SI program is achieving its overall directive of positively assisting student attendees in courses with historically high rates of DWF. Interestingly, *AttFem* had a negative coefficient and was statistically significant at the 10% level. This indicates that, all else equal, females who attended SI were less likely to be observed in a higher grade category. As SI attendees are almost evenly split by gender—438 of attendees were female, versus 449 attendees being male—this was an unexpected result. The negative coefficient could be due to females seeking out SI only after receiving low grades on assignments or midterms, but further research is needed before a definitive conclusion can be drawn.

The demographic independent variables were also primarily statistically significant, and were signed as would be intuitively expected. Both *age* and *married* were positive and significant at the 5% and 10% level, respectively, suggesting that older and married students are more likely to receive higher course grades. This is consistent with the idea that due to the additional demands on their time, students in these groups dedicate their available time to understanding the curriculum—such as through attending SI, as shown in the models above—and subsequently are high performers. Minority students were less likely to be in the higher grade categories, yet the coefficient on *AttMin*, though not statistically significant, was positive. As such, minority students in particular might measurably benefit from exposure to SI. Additionally, students from high schools located in rural Alaska or out of state were less likely to be in a higher grade category than their urban Alaskan peers, with these findings being statistically significant at the 5% and 10% level.

The three proxy variables used for innate academic ability were all found to be positive and statistically significant at the 1% level. This shows that students who scored within the top 10 percentile of the ACT or SAT were inherently more likely to have a high final course grade, as were students with declared STEM majors. Again, these results align with the intuitively expected result.

The model's cutpoint estimates, indicated in Table 6 as the constant cut variables, are shown to be statistically significant as well, with the exception of *cut2*. These values are defined as "the estimated cutpoint on the latent variable [a continuously unobservable mechanism/phenomena] used to differentiate [between *Rfinal* categories] when values of the predictor variables are evaluated at zero." (UCLA, n.d.). Put simply, the cutpoints indicate the probability of a student falling in to any particular grade category. As such, when all independent variables are equal to zero and the value of the latent variable is less than -0.615, the student would be classified as having received an F grade; when the value is greater than -0.615 but less than -0.184, the student would have received a D grade, and so on. As the cuts between F to D, C to B, and B to A are statistically significant, some unobservable factor—in addition to the independent variables—is causing individuals to migrate from one grade category to another.

Table 6. *The Probability of SI and Non-SI Attendee Appearing in Each Rfinal Category*

Grade	Probability of SI Attendee*	Probability of non-SI Attendee*
F	6.38%	14.57%
D	7.34%	12.05%
C	23.21%	28.74%
B	35.30%	30.14%
A	27.77%	14.50%

*Note: All predictors are at their mean values

Based on these cut points, the probability of a student falling into each particular grade category can be calculated. As can be seen in Table 6, the probability of a student who attended SI receiving a passing course grade (defined as a C or higher) is 86.28%, compared to 73.38% of their non-attendee counterparts. Furthermore, the probability of an SI student receiving an A in the course is significantly higher than a non-attendee, with SI attendees being 91.52% more likely to receive an A. On the other end of the spectrum, the probability of an SI student receiving an F is 128.37% *lower* than a student who did not attend SI. When Ds are also included in the calculation, SI attendance decreased a student's probability of receiving a failing grade by approximately 94%. This is a significant finding, and indicates that attending SI has a strong positive effect on student's final course grades, especially among those students who are in danger of not passing a course.

Chapter 6 Conclusion

Based on the observed results of the above models, the SI program at UAF appears to have a positive impact on student final course grades for those individuals who attend. This is particularly true for those students who have a higher probability of failing the course, as SI attendance is shown to decrease the probability of a student receiving a D or an F by approximately 94%. Conversely, attending SI also increased the probability that a student would receive an A by 91.52% over their non-attendee counterpart. Older and married students were consistently found to be more likely to participate in SI, as were students with higher high school GPAs. However, minority groups—including ethnic minorities and females enrolled in the predominantly STEM courses for which SI is offered—do not appear to be actively participating in SI in a significant way, and in the case of *male_min*, actually seem to be less likely to use the program than their peers. As UAF has a significant number of female and Alaska Native students enrolled, this result is troubling. Additionally, it is still unclear whether there are other demographic factors, not captured in the negative binomial regression model, that affect how many SI sessions—if any—a student attends.

To date, the primary limitation on this study has been accessing student demographic and SI attendance records. Further work will be done to collect demographic data for AY15-16 (which will therefore allow for the inclusion of more SI courses in future studies), as well as to fill in missing values in the current dataset for variables such as *SAT10* and *ACT10*. Additionally, if a variable for cumulative GPA can be developed to serve as a proxy for innate intellectual ability and performance, the existing models will have greater explanatory power and subsequently more robust results.

Before a definitive conclusion can be reached as to the overall effectiveness of the UAF SI program, future research needs to be done to control for the potential self-selection bias. It is highly probable that there is unobserved endogenity in models involving student choice in attending SI, as addressed in the literature by Dawson et al. (2014) and others. As such, two-stage modeling techniques need to be employed to first identify why students decide to attend SI, and to then control for those factors when the impact of SI on final course grade is measured. Propensity Score Matching (PSM) techniques can also potentially be employed to help minimize this bias. Though PSM is primarily used for observational studies where randomization of participants receiving the treatment—in this case, SI—is not possible, it has not yet been associated with any SI research.

Despite this study's aforementioned limitations, the systematic approach to capture the factors influencing SI attendance and the program's overall impact on final course grades represents an advancement of the current Supplemental Instruction literature, and can be built upon in the future to help inform universities' student assistance and retention efforts.

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Appendix A

Further Information on Data Collection Procedures

Due to the necessity of accessing sensitive, personally identifiable student data to track student SI attendance, course grades, and demographic information, special permission was sought from the UAF Office of Research Integrity (ORI) and the Office of Admissions and the Registrar before the data collection process began. On September 10th, 2014, the ORI determined that the research goals associated with this project constituted its classification as a program evaluation, and as no students would be directly contacted, it was deemed exempt from review by the UAF Institutional Research Board (Appendix B).

As personally identifiable student information is protected by the Family Educational Rights and Privacy Act (FERPA), it is not viewable or accessible to the general public (Department of Education [DOE], 2015). However, disclosure of student records can be made under several conditions, including releasing pertinent information to "specified officials for audit or evaluation purposes" and to "organizations conducting certain studies for or on behalf of the school" (DOE, 2015). When it has been determined that one or more of the conditions is met, the university can release the data to the appropriate parties without written permission from the student (DOE, 2015).

To assess whether the scope of this study fell under the purview of the exemptions noted above, a meeting was held with the UAF Assistant Registrar, Mike Earnest, and the UAF Graduate School Director, Laura Bender. The intent and ultimate research goals of the SI program review were discussed, as well as clarification of the student information that would need to be gathered to properly conduct a case study. On September 4th, 2014, access to FERPA-sensitive information was granted, with the understanding that all confidential data would remain behind the university's firewall until it could be anonymized (Appendix C). To meet this requirement, each individual student record was assigned a randomly generated identification number—ranging from 1 to 115,000—to be used in place of the University of Alaska student identification number or name. By tracking each record solely through the use of a random identification number, no sensitive information—such as course grades, age, GPA, high school location, etc.—could be recognized as being associated with any one student, thereby preventing the release of personally identifiable student data.

Once the proper permissions were granted, the data collection process began. Each of the three SI centers were contacted, and after proof of IRB and FERPA exemption were provided, SI attendance records were extracted. From Fall 2014 to Fall 2015, both past and current records were collected, resulting in information on SI courses from Fall 2010 to Spring 2015. As each center has its own internal record keeping process—and, based on staff turnover, these varied over time within the centers as well—it was necessary to adopt a standardization procedure. First, each unique course—defined as one course number offered in one semester—and, if applicable, its sections, was separated into its own individual Excel spreadsheet file. It should be noted that each file was encrypted, and the passwords were kept on a printed, not electronic, document that was secured in both the thesis advisor's and student's offices. From there, the final course grade for each student was inputted. Though midterm grades were available and captured for some students, they were not assigned consistently. This is due in large part to individual instructor preference, as well as UAF only requiring that midterm grades be assigned to freshmen students; reporting midterm grades for all other student groups is strictly optional (UAF, 2016a). As such, this information was recorded where available, but ultimately was not used as a variable in the final data models.

After grades were appropriately matched to each student in the course, SI attendance was reviewed. Again, as each center reported data differently, attendance records ranged from notating each date that an SI session was held during the semester and which students attended, to having a single column with the overall number of sessions each student attended. This information was then broken down into three distinct metrics: a binary variable indicating whether a student attended one or more sessions during the semester, a total attendance variable with the number of sessions attended, and a set of categorical variables separating attendance into six different groupings.

As student information at all University of Alaska campuses is stored and maintained within a protected, system-wide database, the UAF Student Records Manager assisted in pulling data. Due to the time-intensive nature of only accessing the records of those students enrolled in courses in which SI had been offered, data was reported for all students enrolled in one or more credits at UAF for each semester from Spring 2011 onward. The demographic data from each semester was then matched to the students in each SI course from the same semester.

Once all attendance and demographic records had been combined in the individual course Excel files, a master dataset was created. As all data records had been tracked by the student's UAF identification number, not name, in the course files, students who had been enrolled in more than one SI course could be tracked in the master dataset. These student records were grouped together, if applicable, allowing all unique UAF identification numbers to be assigned a new number using Excel's random number generator. After the random identification numbers were in place, all UAF student identification numbers were deleted, and the remaining variables were transferred to a new spreadsheet. As such, the data was fully anonymized, thereby complying with FERPA and UAF standards, and allowing for further data analysis to be conducted outside of the UAF firewall. A list of all dataset variables used in subsequent analysis can be found in Table 2.

Further information on the composition of the master dataset can be found in the tables below. In the first of these, Table A-1 showcases the number of observations and subsequent percentage for each value of the *Total_Attended* variable.

Table A-1. *Total Number of SI Sessions Attended*

Total_Attended		
Total Sessions Attended	Number of Observations	Percentage
0	2,194	71.21%
1	388	12.59%
2	192	6.23%
3	86	2.79%
4	58	1.88%
5	34	1.10%
6	27	0.88%
7	24	0.78%
8	22	0.71%
9	10	0.32%
10	4	0.13%
11	9	0.29%
12	2	0.06%
13	4	0.13%
14	7	0.23%
15	5	0.16%
16	1	0.03%
17	6	0.19%
18	1	0.03%
19	3	0.10%
20	0	0.00%
21	2	0.06%
22	1	0.03%
23	1	0.03%
Total	3,081	100.00%

In order to increase the number of observations found within any one grouping—particularly among the categories with the highest number of sessions attended—six broad categories were created. Table A-2 indicates the number of observations found in each.

Table A-2. *SI Attendance by Category*

AttendCat		
Attendance Category	Number of Observations	Percentage
Never Attended	2,194	71.21%
Attended Once	388	12.59%
Attended 2-3 times	278	9.02%
Attended 4-5 times	92	2.99%
Attended 6-10 times	87	2.82%
Attended 11+ times	42	1.36%
Total	3,081	100.00%

Table A-3 provides a count of the number of individuals in each ethnicity group attending UAF as self-reported by students on their admission application.

Table A-3. *Dispersion of Ethnicity Within Dataset*

Ethnicity	Number of Unique Observations	Percentage of Observations
Alaska Aleut	4	0.21%
Alaska Indian (Athabascan)	39	2.08%
Alaska Eskimo (Inupiaq)	25	1.33%
Alaska Eskimo (Yupik)	27	1.44%
Alaska Eskimo (Other)	3	0.16%
Alaska Indian—Haida	1	0.05%
Alaska Indian—Other/Unspecified	1	0.05%
Alaska Indian—Tlingit	3	0.16%
Alaska Native Southeast	2	0.11%
Alaska Native (Other/Unspecified)	13	0.69%
American Indian or AK Native	20	1.07%
American Indian (Non-AK Native)	5	0.27%
American Indian and White	3	0.16%
Asian	37	1.97%
Asian/Pacific Islander	32	1.71%
Asian and White	2	0.11%
Black, Non-Hispanic	24	1.28%
Black and White	1	0.05%
Hispanic or Latino	58	3.09%
Native Hawaiian/Other Pacific Islander	5	0.27%
White, Non-Hispanic	1,091	58.16%
Other	28	1.49%
Decline to State	161	8.58%
Student Refused	4	0.21%
Unknown/Not Specified	287	15.30%
Total	1,876	100.00%

Table A-4 shows the individual components of the three broad ethnic categories created to increase the number of observations in each grouping, as well as the associated number of total observations.

Table A-4. *Main Ethnicity Categories and Subcategories*

Ethnicity Categories	Ethnicities	Total Number of Unique Observations
White	White	1,091
Minority	Native, Asian, Black, Hispanic	305
Hispanic	Hispanic	58
Black	Black, Black and White	25
Asian	Asian/Pacific Islander, Asian, Asian and White	71
Native	AKNative, Amerin, Native Hawaiian/Other Pacific Islander	151
Amerin	American Indian (Non-AK Native), American Indian and White	8
AKNative	Alaska Aleut, Alaska Native (Other/Unspecified), Alaska Eskimo (Athabascan), Alaska Eskimo (Yupik), American Indian or AK Native, Alaska Eskimo (Other), AK Native Southeast, Alaska Indian—Haida, Alaska Indian—Other/Unspecified, Alaska Indian—Tlingit	138
Ethunk	Decline to State, Other, Student Refused, Unknown	480

Another important demographic factor is the location of the high school each student graduated from. Through the method for categorizing each location is discussed above, the dummy variables were included in the dataset as a means of identifying whether geographical background had any influence on a student's decision to attend SI, as well as to serve as a potential indicator for academic preparedness. The number of observations for each category is presented in Table A-5.

Table A-5. *Dispersion of Graduation High School Locations*

Variable	Total Number of Observations	Percentage	Total Number of Unique Observations	Percentage
hsrural	689	22.36%	433	23.04%
hsurb	1,503	48.78%	865	46.04%
hsout	728	23.63%	479	25.49%
hsint	71	2.30%	46	2.45%

It is also of interest to examine each demographic variable in relation to SI attendance. As Table A-6 shows, no variable had an attendance rate of more than roughly a third, but there was variability between similar groups. For example, more females attended than males, and white students had higher attendance than minority students. Also, the largest attendance rate observed among the high school variables was for students who graduated from high schools outside of Alaska (30.77%), with students from rural Alaskan high schools having the lowest attendance rate (26.12%).

Table A-6. *SI Attendance Rates by Demographic Variable When the Variable is =1*

AttendD Demographics					
Variable	**Attended**	**Percentage**	**Did Not Attend**	**Percentage**	**Total Observations**
AttendD	887	28.79%	2,194	71.21%	3,081
Female	438	30.52%	997	69.48%	1,435
Male	449	27.28%	1,197	72.72%	1,646
White	523	28.52%	1,834	71.48%	1,834
Minority	132	26.24%	371	73.76%	503
Native	68	27.10%	183	72.91%	251
AKNative	61	27.73%	159	72.27%	220
STEM	555	29.57%	1,322	70.43%	1,877
SAT10	12	17.65%	56	82.35%	68
ACT10	42	20.69%	161	79.31%	203
hsrural	180	26.12%	509	73.87%	689
hsurb	425	28.28%	1,078	71.72%	1,503
hsout	224	30.77%	504	69.23%	728
hsint	21	28.17%	51	71.83%	71

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Appendix B

UAF Institutional Review Board Approval

UNIVERSITY of ALASKA

Alyssa Englert <aenglert@alaska.edu>

IRB Thesis Research Review--Englert

Gretchen Hundertmark <ghundertmark@alaska.edu> Wed, Sep 10, 2014 at 9:46 AM
To: Aly Englert <aenglert@alaska.edu>

No, you don't need to do anything else. Keep this email so that when you are doing your final grad paperwork you have proof that you checked with me.

Gretchen

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Gretchen L. Hundertmark, CRA
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"Good character is more to be praised than outstanding talent. Most talents are, to some extent, a gift. Good character, by contrast, is not given to us. We have to build it piece by piece - by thought, choice, courage and determination."
~ John Luther

On Wed, Sep 10, 2014 at 9:38 AM, Aly Englert <aenglert@alaska.edu> wrote:
Hi Gretchen,

Okay, great! Do I need to do anything further in regards to notifying IRB or any other unit on campus, or can I start collecting data later this week?

Best,
Aly

On Wed, Sep 10, 2014 at 9:35 AM, Gretchen Hundertmark <ghundertmark@alaska.edu> wrote:
This looks like program evaluation and you don't need IRB review.

Gretchen

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On Wed, Sep 10, 2014 at 9:32 AM, Aly Englert <aenglert@alaska.edu> wrote:
Hi Gretchen,

No--it will be all second hand data collection. I'll only be reviewing their attendance records for each class and accessing the demographic data we have on them in Banner. I'm also working with Crystal Goula before she leaves to make sure I'm going about collecting the Banner/Toad data reports correctly.

Best,
Aly

On Wed, Sep 10, 2014 at 9:25 AM, Gretchen Hundertmark <ghundertmark@alaska.edu> wrote:
Will you be contacting the students?

Gretchen

<>><((((º>`•.¸¸.•´¯`•...¸><((((º>`•.¸¸.•´¯`•...¸><((((º>
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~ John Luther

On Wed, Sep 10, 2014 at 9:18 AM, Aly Englert <aenglert@alaska.edu> wrote:
Hi Gretchen,

Early in May, I spoke with you on the phone regarding my research topic for my thesis. I will be looking at the Supplemental Instruction program at UAF, and evaluating both its effectiveness and the types of students who utilize the program.

When we spoke, you said that my topic would be classified as a program review, and as such I would not have to go through the full IRB review process. However, you did request that I submit an explanation of my thesis in writing, which I have attached here. Also included in the attachment is a copy of the e-mail correspondence between myself and Mike Earnest in the Registrar's Office granting me FERPA access to student demographic data.

Please let me know if you have any questions regarding my research summary or proposed research. I have not yet collected any data, and will not do so until I have IRB approval. If you need me to provide anything further, please let me know and I am happy to do so.

Best,
Aly

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Appendix C

UAF Registrar's Office FERPA Approval

Alyssa Englert <aenglert@alaska.edu>

Request for FERPA Access, SI Program Review

Mike Earnest <wmearnest@alaska.edu> Thu, Sep 4, 2014 at 2:46 PM
To: Aly Englert <aenglert@alaska.edu>
Cc: Joseph Little <jmlittle2@alaska.edu>, Laura Bender <lebender@alaska.edu>

Hi Aly,

Please accept my apologies for the delay in responding. I was out of town for a family emergency for most of August.

As we discussed, I do approve of your request to collect and use the student data for your study, as outlined in the email above. Please just keep the information behind the UA firewall as long as ID numbers are attached. Once you assign random numbers to the students, you can do what you need to analyze the data, although any particular student's record should still remain confidential.

Thanks for taking the time to explain your project, and let me know if you have additional questions.

Mike Earnest

On Wed, Aug 13, 2014 at 2:50 PM, Aly Englert <aenglert@alaska.edu> wrote:
Good afternoon,

Thank you for meeting with me on August 1st. I apologize for my delayed response--I was determining the variables I will need for my program review with my thesis advisor, and wanted to make sure that I sent you an accurate request for student data.

As mentioned in our prior meeting, I am currently both a UAF employee and an enrolled graduate student. I am working on my thesis, which is a program review of the UAF Supplemental Instruction (SI) program with a subsequent economic analysis. I will be looking at historical UAF SI data--which, to the best of my knowledge, extends from 2010 onward--to see whether or not attending SI sessions improved a student's grade in the course, and ultimately assisted them in graduating. Additionally, I will be trying to infer some of the underlying causes that lead to students deciding whether to attend SI sessions or not. By doing so, I hope to help identify ways to bolster SI attendance among UAF students, should the SI program empirically prove to be beneficial (as I hypothesize it is).

In order to complete a comprehensive review, I would like to request access to attendance records held by SI program directors across the UAF campus, as well as transcript data for students who were enrolled in a course offering SI from 2010 onward. This includes: cumulative GPA, declared major, term GPA for the semester in which a student was enrolled in a course offering SI, student's ultimate grade in the course offering SI, whether the student transferred to UAF from another institution, graduation status, and semesters attended at UAF.

I would also like to collect demographic data, to include: ethnicity, whether the student received any form of financial aid (will be represented in a simple binary variable), citizenship, marital status, veteran status, date of birth, age at graduation, and gender.

Finally, I would like to collect background data on prior academic performance and aptitude, to include: location data on the high school the student graduated from, high school graduation year, high school GPA, class rank/size/percentage (if available), SAT scores, and ACT scores.

In order to collect this data, I will need access to student ID numbers, which I realize are not directory data. However, after all relevant data for my program review has been collected, I will scrub my data set of all identifiable information--namely student ID numbers--and will assign a random number to each observation instead. No data set with identifiable student data will be published.

In the first week of May 2014, I spoke with Gretchen in the Institutional Review Board, and they will be classifying my research as a program review. I will be working with the IRB independently to ensure all research ethics, standards, and protocol are met.

Given that my research is meant to improve instruction within those courses offering SI and benefit the UAF student population as a whole, do you approve my request to FERPA data?

Best,
Aly

--
Aly Englert
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